Tools for Measuring and Understanding the Proximity of Users to Their Smartphones

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ABSTRACT

Two studies in ubiquitous computing examined users' proximity to their smartphone in 2006 and in 2011 [7, 14]. Both studies have used a passive data collection tool and the day reconstruction method [8]. Additionally, Dey at al. adopted an online survey to validate their findings with a larger population sample. In 2019, we attempted to revisit this research topic due to the high adoption rate of smartphone and smartwatch. In our replication study, we developed a new passive data collection tool and a novel survey technique, proximity-based ecological momentary assessments. We also adopted the day reconstruction method and online survey utilized in the previous studies. This technical report presents the details of the research tools and techniques used in our study.

CCS CONCEPTS

• **Human-centered computing - Ubiquitous and mobile computing - Empirical studies in ubiquitous and mobile computing**;

KEYWORDS

Proximity Measurement, Ecological Momentary Assessment, EMA, Day Reconstruction Method, DRM, Proximeter, Smartphone,Smart Devices

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Georgia Institute of Technology, 2020, Atlanta, GA, USA

Reference Format:
Jung Wook Park, Hayley I. Evans, Hue L. Watson, Gregory D. Abowd, and Rosa I. Arriaga. 2020. Tools for Measuring and Understanding the Proximity of Users to Their Smartphones. *Technical Report. Georgia Institute of Technology*. Atlanta, GA, USA, 9 pages.

1 INTRODUCTION

Smartphones are pervasive among nearly all demographics in the United States. 81% of Americans are smartphone owners in 2019 [15]. Due to the pervasiveness of smartphone across a wide range of groups and individuals, research in ubiquitous computing has frequently adopted a smartphone as a lens to explore human behaviour, physical health, mood, and so on [3, 4, 10, 17, 19]. However, Patel et al. and Dey et al. found that smartphone owners did not consistently use, carry, or have access to their phones throughout the day in 2006 and 2011, respectively [7, 14]. In order to understand smartphone owners' usage patterns, previous studies have used passive data collection and the day reconstruction method (DRM) [8]. Additionally, Dey at al. employed an online survey to validate their findings with a larger sample of 367 smart phone users. In our study to understand user proximity to smartphones, we have adopted four techniques — passive data collection, DRM, ecological momentary assessments (EMA), and online survey.

In this technical report, we describe our updates to the measurement devices and tools used in our proximity study. In Section 2 - 6, we present new wearable devices, examine theoretical models of radio frequency signal propagation and noise cancellation techniques, and discuss data collection and visualization tools. Section 7 gives a brief overview of DRM, and Section 8 explains the motivation and operation of EMA. Lastly, Section 9 and Appendix A describe the questions and answers of the online survey.

Note that we refer Patel et al. and Dey et al.'s papers frequently in this technical report. Thus, we did mention the sources without citation. Please refer [7, 14] in the bibliography for more details about these sources.

2 DEVELOPING NEW SENSORS TO IMPROVE PROXIMITY DETECTION - PROXIMETER BAND AND TAG

Patel et al. and Dey et al. used pendant-style Bluetooth devices worn as a lanyard around the participant's neck. However, given the limited sensing capabilities of the pendants, there was no indication of when the pendant was being worn by the participant. Both studies compensated by having participants self-report when they removed the pendant, with the obvious concerns for the accuracy of self-report over what was a 2-3 week study period. We aim to improve upon this data collection by creating two Bluetooth Low Energy (BLE) devices, Proximeter Band (pBand) and Proximeter Tag (pTag), that record on- and off-body status.

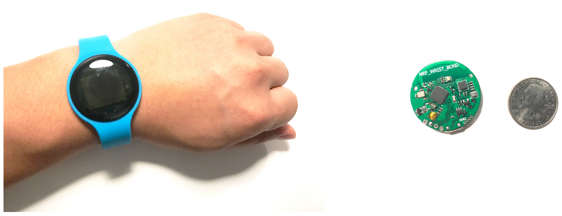

Figure 1: Proximeter Band: (left) the apparatus of the pBand, (right) size comparison with a US Quarter

pBand is a wrist-worn device that was distributed to participants who did not own an Apple Watch. This device is capable of communicating with an iPhone over BLE, inferring motion using a three-axis accelerometer, and displaying the status of the device through a LED indicator (see Figure 1). It measures acceleration data and battery levels, transmitting them to the connected iPhone every 10 seconds. We determined whether a participant wore the device by checking variations of the root-mean-square (RMS) value of the three-axis acceleration during a 10-minute window. If the battery level of the device was less then 20%, we sent a notification reminder via iPhone and asked the participant to recharge the device.

Although Apple Watch is technically capable of measuring proximity to the connected iPhone, the APIs are not publically available to third-party developers. Therefore, we developed pTag, a BLE device which can be attached to the strap of an Apple Watch and allowed us to measure proximity between the iPhone and Apple Watch. We covered the surface of the pTag using a water-resistant, plastic case to minimize behavioral changes to a user's normal routine. Since Apple Watch allows measurement of heart rate for at

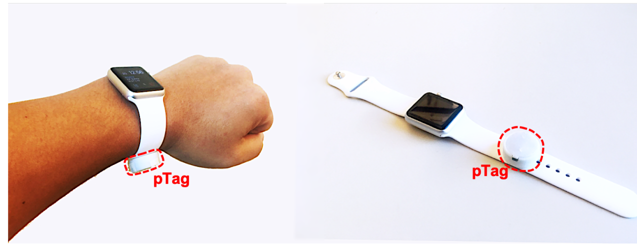

Figure 2: Proximeter Tag on Apple Watch: as it appears when worn (left) and on flat surface

least every 10 minutes while it is worn, we utilized the existence of heart rate data to verify whether a user was wearing the watch or not. As a result, we were able to exclude the motion sensing on pTag, which significantly reduced power consumption. The battery life is approximately 3 months, so participants did not need to charge it over the period of the study.

Similar to Dey et al.'s study, we wanted to categorize the distance measured between user and phone into three zones: within arm's reach (0 - 2 meters), within the same room (2 - 6 meters), and beyond room level (beyond 6 meters, including the condition of no pBand or pTag connection). The following two sections describe how we arrived at that continuous measurement. After describing the iPhone software platform that collected data for our study, we describe how we used the continuous distance measure to define the context of meaningful separation events used to trigger the notifications of EMA.

3 CONVERTING RF SIGNAL STRENGTH TO DISTANCE

Radio signals follow an inverse square law, which states that the power density of the signals is proportional to the inverse square of the distance. In an ideal environment, the distance is the only factor that affects signal strength. However, various environmental factors also affect the attenuation of a signal, such as the human body, humidity, metal objects, and other obstacles. To consider these factors, an exponential model or log-distance path model has been widely adopted to represent the relationship between received signal strength indication (RSSI) and distance [9]:

$$RSSI_{dBm} = -10_n \log 10d + A \quad (1)$$

Where d is a distance value, and n (normally 2 in an open space) is an attenuation factor. A can be determined by environmental noise factors and antenna gains of the transmitter and the receiver. This equation can be converted to:

$$d = \alpha e^{\beta RSSI_{dBm}} \quad (2)$$

To determine the values of variables α and β empirically, RSSI values are measured in different distances and averaged to obtain optimal α and β values [11]. Thus, we had a calibration session to determine propagation coefficient values for each participant. We placed the iPhone in a fixed point and asked the participant, who was wearing a pBand or an Apple Watch with pTag, to move to six different distances (i.e., 0, 1, 2.5, 5, 7.5, and 10 feet), maintaining each distance for 1 minute. We collected RSSI values at 1 Hz for each distance. Figure 3 presents an example of test calibration data.

4 FILTERING OUT NOISE SIGNALS

Multipath reflections, caused by walls and other objects (including people) around the pBand/pTag, produce unexpected fluctuations of RSSI values and introduce significant errors in distance estimation [11]. Therefore, it is necessary to filter out noise signals to minimize the errors. We explored four signal processing filters which have been widely adopted in the areas of wireless communication and RF signal strength measurement, including 1-D Median, 1-D Kalman and moving average filters [6, 13]. Deak et al. ascertained that a 1D median filter outperformed five-point Triangular Smoothing Algorithm, Savittzky- Golay filter, and Kalman filter regarding an error rate [6]. While, in other experiments, Kalman filters showed the lowest error in filtering RSSI values compared to an average filter and a median filter [16]. As such, we examined these filters to find the best-fit for our study.

Exponential Weighted Moving Average Filter (EWMA)

This filter requires a small number of previous samples and can efficiently discount the contribution of preceding values in the running value [13]. A mathematical model of the filter is :

$$y_t = \alpha y_{t-1} + (1 - \alpha)x_t \tag{3}$$

where y_t is the filtered outcome at time t, x_t is the measured RSSI value at time t, and α is a parameter controlling the smoothness of the filter. α is ranging from zero to one, and the optimum parameter depends on the amount of noise. Large values of α will lead to very smooth outcomes, while small values of α will lead to highly responsive results.

Autoregressive Moving Average Filter (ARMA)

We chose this filter as a broadly-used open source beacon library, AltBeacon, used this filter to smooth RSSI values [12]. Since this filter did not require a long averaging process to update latest values in each iteration, it quickly responded to changes. This filter has the following form:

$$y_t = y_{t-1} - \alpha(y_t - x_t) \tag{4}$$

Where y_t is the filtered outcome at time t, x_t is the measured RSSI value at time t, and α is a constant to configure how much the newly measured value can impact existing values. Large values of α will lead to quicker responses, while small values of α will lead to more susceptible responses to fluctuations.

1-D Median Filter

This filter performs well for removing spike noise [6]. It examines the RSSI value by value and replaces each value with the median of entries in a given window. The only configurable value of the filter is the size of the window.

1-D Kalman Filter

Like other filters, the Kalman filter is widely adopted for removing a large part of the noise from the data and estimating the optimal state of the data [2, 16]. The downside of the Kalman filter is that a system needs to scarify a bit of its responsiveness since it requires a recursive operation to take the previous measurements into account. Since Bulten et al. used a Kalman filter in a similar environment like ours, we replicated their transition and observation models. Since we have no control, we set zero to the control vector of the filter. Similar to Bulten et al.'s filter settings, we set i) one to the state and measurement vectors, ii) the variance of the RSSI values to the measurement noise, and iii) 0.008 to the process noise.

To compare the four filters above, we collected RSSI values between an iPhone and a pBand in five different distances (i.e., 0.5, 2.5, 5, 7.5, and 10 feet) during five minutes for each distance. There were no moving objects in the testing environment. As we discussed in Section 3, the distance between two devices is the only factor that can change RSSI value. It means that the standard deviation of the measured RSSI values for each distance should be close to zero. Since the filtered values should follow a logarithmic regression [9], we also built a regression model from the values and examined how the values can fit into the model using a R^2 value. The result showed that 1-D Kalman filter outperformed other filters based on the two criteria, standard deviation and R^2. (See Table 1).

5 DEVELOPING A MOBILE APPLICATION ON IPHONE - PROXIMETER APP

We developed an iOS application, Proximeter App, for this study which consists of various sensing, operation, and data management modules (See Figure 4). In this section, we describe components of this application.

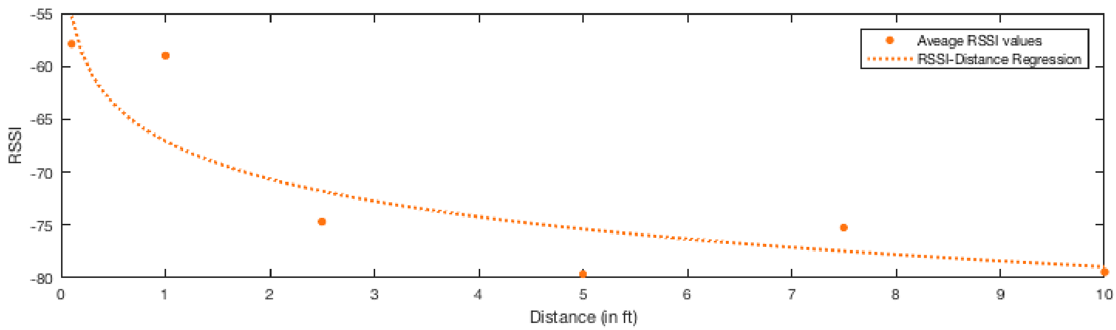

Figure 3: An example data to determine propagation coefficients α and β

Table 1: A comparison of four widely-used filters (Mean: The mean value of the measured RSSI values in dBM, SD: Standard deviation of the values, ARMA: Autoregressive Moving Average Filter, EWMA: Exponential Weighted Moving Average Filter)

	No Filter		ARMA		EWMA		1-D Kalman		1-D Median	
Distance	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
0.5	-52.29	24.99	-48.09	4.96	-52.72	4.87	-51.47	3.66	-42.7	15.67
2.5	-64.93	15.39	-59.86	5.54	-64.34	5.61	-60.16	5	-64.93	15.39
5	-77.38	10.65	-72.93	5.02	-77.1	5.23	-73.15	5.41	-77.38	10.65
7.5	-74.94	10.73	-70.68	5.35	-75.02	5.41	-75.69	4.68	-74.94	10.73
10	-76.79	12.26	-72.36	5.6	-76.84	5.61	-76.2	4.65	-76.79	12.26

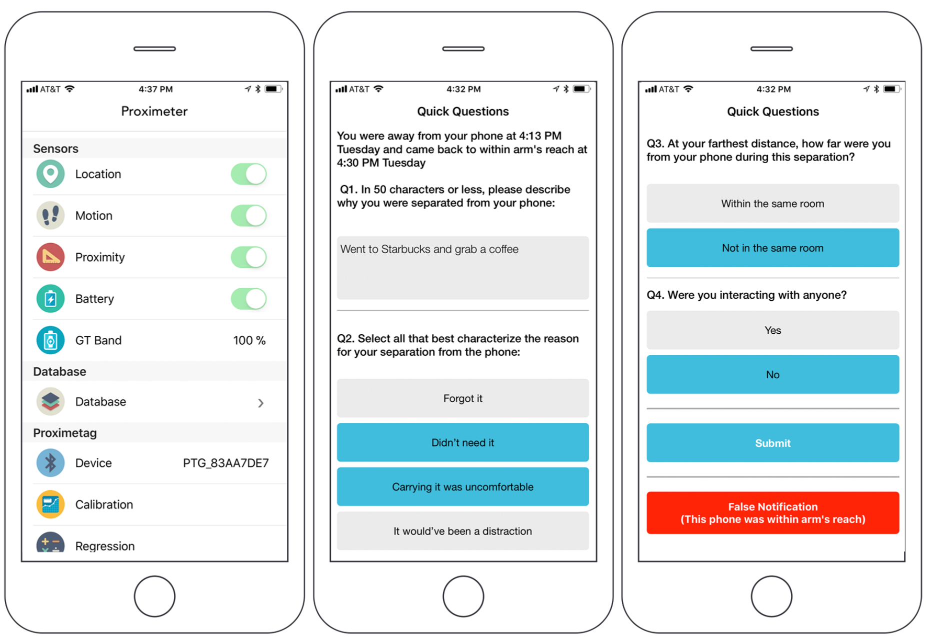

Figure 4: User interfaces of the Proximeter App: the main view (Left), an EMA view (EMA, Center and Right)

Phone Location Sensing. This module measures the latitude, longitude, altitude, speed, and accuracy of the iPhone's location. We configure the desired accuracy as three kilometers which allows iOS to handle location sensing sources including GPS hardware, cell radios, or Wi-Fi, in a flexible and power-efficient way. This module also captures location once the app detects important situations including users' separation and reunion events (discussed later) from their smartphone or charging events.

Phone Motion Sensing. This module records motion data of the phone from Apple's sensor fusion algorithm [1]. When this iOS API detects changes in the activity state, it returns the new state to the module. The inferred motions are stationary, walking, running, cycling, automotive and unknown.

Phone Battery Sensing. This module collects the battery percentage and state information (e.g., unplugged, charging, full) of the phone provided by an iOS API.

Bluetooth Proximity Sensing. If a pBand or pTag is within communication range of the phone, approximately 10 meters in open space, this module measures the RSSI of that BLE device every 10 seconds. This module then converts RSSI values into distances by using the conversion method discussed in Section 3.

pBand Sensing and Status. pBand senses three-axis acceleration every 10 seconds and transmits the data to this module. Once the module receive the accelerometer data, it computes the RMS value and records both raw and processed data for determining whether the user is wearing pBand. This module also records the battery status of pBand every 10 seconds.

Watch-on-wrist Sensing. As we described in the Section 3.1, Apple's HealthKit framework measures a user's heart rate at least every 10 minutes while wearing Apple Watch. If there are available heart rate data in the database of the framework, this module extracts only timestamps of heart rate data and records them. By checking the existence of timestamps, we can detect whether the user is wearing the Apple Watch.

Data sync. In order to reduce the power consumption of the app, we first store all the sensing data into a local SQLite database on the iPhone. We then apply two rules to upload the stored data to our study server. First, the iPhone must be charging and have a Wi-Fi connection. Second, a data sync command is sent to the iPhone through an Apple silent push notification. This rule is executed to generate a graph (See Figure 6) for interview sessions which will be discussed in the next section.

6 DEVELOPING A VISUALIZATION TOOL - PROXIMETER VIEW

Patel et al. and Dey et al. interviewed participants about their proximity to their smartphone once a week. Similar to the past two studies, we developed a visualization tool to assist with the interview sessions. Rather than providing visualization materials to participants, we extracted all the important episodes from the visualization tool and checked whether there are missing or inconsistent data between the collected data and the information what participants answered. Figure 5 shows an example of the graph we generated using the visualization tool.

7 USING DAY RECONSTRUCTION METHOD (DRM) TO GATHER RICH QUALITATIVE DATA

Both Patel et al. and Dey et al. utilized DRM in their studies [8]. In this method, users are asked to recount the previous 24 hours in a qualitative interview. Users may use calendars, diaries, or other aids to assist in the reconstruction of their days. Participants met with our team once per week via phone to discuss their activities on a different day of the week for all four weeks of the study. Our team had participants walk us through their days, step-by-step, focusing on phone and/or technology usage, phone proximity, and their activities. In addition, our team members carefully examined the data from the 24-hour period immediately before the interview, identifying points of separation, reunion, and missing data. We developed a list of 2-5 questions based on the collected data.

8 DEVELOPING AN ECOLOGICAL MOMENTARY ASSESSMENT TO REDUCE PARTICIPANT BURDEN

Self-report as a data collection technique has its clear drawbacks, and the original Patel et al. study raised concerns about how to get participants to recount accurate reasons for separation from their mobile phones. While the DRM was useful for getting rich and reliable self-report accounts, they found it was burdensome for participants. Therefore, in an effort to explore how we might reduce this user burden and collect more timely information regarding user activities, we employed EMA that minimize recall errors and maximizes ecological validity in real-world settings [18]. EMA have been widely adopted to assess events in participants' lives by using random sampling, electronic diaries, or sensors [5]. An issue for delivering EMA is to trigger them at the right time; in our case, that would mean being able to ask a participant about the reason a separation from their phone right after they had been reunited with it. Our EMA were designed to be triggered at that moment of reuniting with the phone after a separation. Figure 6 shows how we defined *Separation* and *Reunion* events. *Separation* is defined as when a participant is six meters away from their phone for more than three minutes, and *Reunion* means when a participant comes back within two meters of the phone after the separation. EMA were designed to be delivered at the point of reunion. To reduce user interruption, we limited EMA to be at most once per hour and never between the hours of 12am - 6am. The two images in the right side of Figure 4 show the interface of EMA which includes the questions and answers in Table 2.

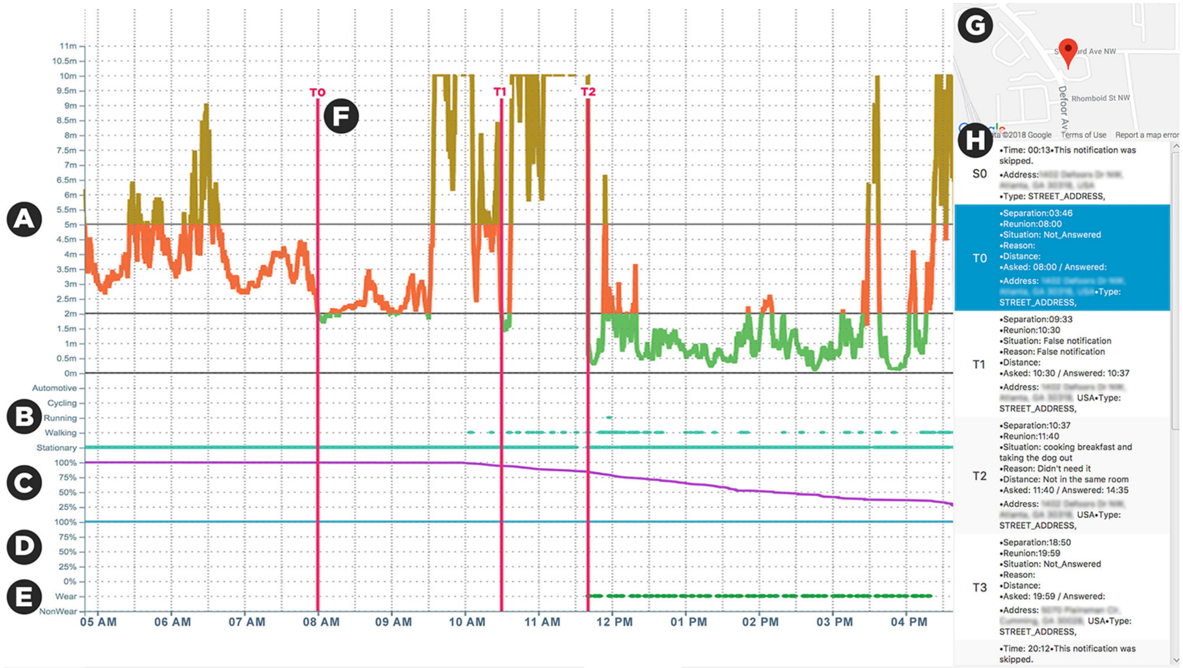

Figure 5: A graph of the data visualization tool which presents one day of the experiment. (A) Proximity Data: The participant's proximity to his/her iPhone in meters. In the proximity line, we changed color of the line to indicate their ranges: 0-2m as light green, 2-6m as orange and beyond 6m as gold. (B) The next cyan-colored dots show the motion status of the iPhone (i.e. Stationary, Walking, Running, Cycling, and Automotive). (C) The purple-colored line describe the battery level of the iPhone. (D) The blue-colored line illustrates the battery level of pBand or pTag. The participant wears the Tag in this example, so that its battery level was not changed as we mentioned in Section 3.1. (E) The dark green-colored dots show the status of whether the participant wears Proximeter Band or Apple Watch. (F) Red-colored vertical lines in the graph denote moments in which the application triggers EMA notifications (e.g. T1, T2, ..., Tn) or skips them (e.g., S1, S2, ... Sn). This will be discussed later in the paper. (G) The map displays the location of the event highlighted in the list below. (H) The list of separation and reunion events helps researchers to understand the details of the moments and extract critical episodes.

Table 2: Questions and answers of EMA

No	Question	Answer
1	In 50 characters or less, please describe WHY you were separated from your phone and WHERE	Text input Box
2	Select all that best characterize the reason for your separation from the phone. (Select multiple items)	1) Forgot it, 2) Didn't need it, 3) Carrying it was uncomfortable, 4) It would have been a distraction, 5) I was in a phone restricted area, 6) Other: (Please explain briefly)
3	At your farthest distance, how far were you from your phone during this separation?	1) Within the same room, 2) Not in the same room
4	Were you interacting with anyone?	1) Yes, 2) No

EMA Answers

EMA were deployed in the second and fourth weeks only between 6AM and 12AM. This was done to ensure that the hourly, short-questionnaires did not alter behavior during the study period. The questions of EMA were sent at most once per hour and when a separation and reunion to the phone were detected, as described earlier. Participants were asked to provide a short explanation for their activity, why they chose to leave the phone behind, and if they were interacting with others.

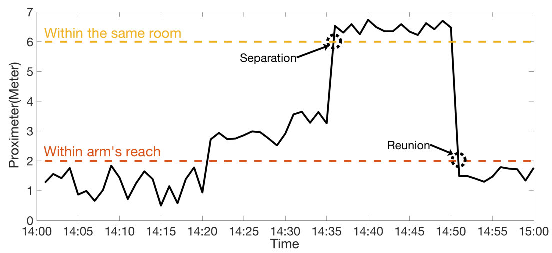

Figure 6: Separation and reunion conditions of EMA

Participants received 722 EMA notifications in weeks two and four in our study. Of these, 180 were marked as false positive notifications, 300 received responses, and 242 were not answered. When participants were separated from their phones they were asked their farthest distance from the phone. 207 responses indicated that the users were not within the same room whereas 93 were in the same room. They were also asked whether or not they had any social interaction during this time. Roughly half of the users responded that they had a social interaction (133 versus 167 that indicated no social interaction). Finally, participants were asked to select the reasons which best characterized the separation. The response selected most often was "Didn't need it." A full summary of responses selected are presented in Table 3.

Table 3: Reasons which characterized separation from the results EMA

Reason(s)	Number of Times Selected
Carrying it was uncomfortable	45
It would've have been a distraction	57
Other	25
Didn't need it	207
I was in a phone restricted area	31
Forgot it	12

Measuring behavior changes by EMA

When we designed the user study, we were concerned that delivering EMA notifications may change the behavior patterns of participants and the proximity to their smartphone. Thus, we only used EMA in the weeks two and four and measured statistical significance of the proximity between first and second weeks and between third and fourth weeks. We found that there were no statistically significant changes in participants' proximity to their smartphone when we used EMA (p-values of all t-tests > 0.05). See Figure 7 and Table 4.

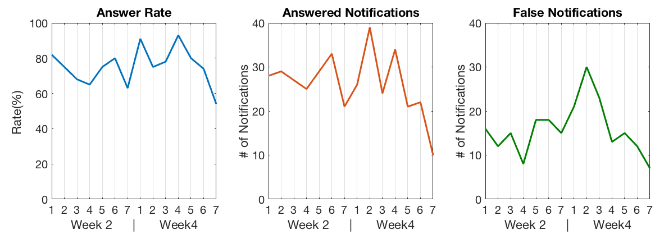

Figure 7: We computed the answer rate of EMA(left), the number of answers without false notification(middle), and the answer of false-positive notifications(right) across all participants.

Table 4: Proximity changes over the course of the study

	Within Arm's Reach	Within the same room	Beyond room level
Week 1 (No EMA)	58.06	15.77	26.17
Week 2 (EMA)	54.21	16.51	29.28
Week 3 (No EMA)	50.18	15.96	33.86
Week 4 (EMA)	50.85	13.69	35.46

9 ONLINE SURVEY

We employed a online survey to validate our findings with a larger sample size. This survey also allowed us to include other phone brands (e.g., Android, Blackberry) as well as Android-wear watch users. The details of the online survey are presented in Appendix A

10 CONCLUSION

We have discussed the measurement tools and techniques that used in the emprical investigation of users' proximity to their smartphone. Compared to the previous studies, we developed new data collection and visualization tools and improved the quality of collected data by considering on-/off-body status. To overcome the shortcomings of passive data collection, we developed a proximity-based EMA technique and combined it with the DRM for qualitative analysis. Lastly, we adopted an online survey to ensure a fact that our research findings were in line with a larger population sample. All the details of the user study and findings will be presented in our paper, *Growing Apart: How Smart Devices Impact User's Proximity to Their Smartphone*, in the IEEE Pervasive Computing magazine.

REFERENCES

[1] Apple Inc. 2018. *Core Motion API*. https://developer.apple.com/documentation/coremotion/cmmotionactivity

[2] Wouter Bulten, Anne C van Rossum, and Willem F G Haselager. 2016. Human SLAM, Indoor Localisation of Devices and Users. *IoTDI* (2016), 211–222. https://doi.org/10.1109/IoTDI.2015.19

[3] Luca Canzian and Mirco Musolesi. 2015. Trajectories of Depression: Unobtrusive Monitoring of Depressive States by means of Smartphone Mobility Traces Analysis. In *the 2015 ACM International Joint Conference*. ACM Press, New York, New York, USA, 1293–1304. https://doi.org/10.1145/2750858.2805845

[4] Zhenyu Chen, Mu Lin, Fanglin Chen, Nicholas D Lane, Giuseppe Cardone, Rui Wang, Tianxing Li, Yiqiang Chen, Tanzeem Choudhury, and Andrew T Campbell. 2013. Unobtrusive sleep monitoring using smartphones. In *The 7th International Conference on Pervasive Computing Technologies for Healthcare*. ICST (Institute for Computer Sciences, Social-Informatics and Telecommunications Engineering), 145–152. https://doi.org/10.4108/icst.pervasivehealth.2013.252148

[5] S Consolvo and M Walker. 2003. Using the experience sampling method to evaluate ubicomp applications. *IEEE Pervasive Computing* 2, 2 (April 2003), 24–31. https://doi.org/10.1109/MPRV.2003.1203750

[6] Gabriel Deak, Kevin Curran, and Joan Condell. 2010. Evaluation of Smoothing Algorithms for a RSSI-Based Device-Free Passive Localisation. In *Image Processing and Communications Challenges 2*. Springer, Berlin, Heidelberg, Berlin, Heidelberg, 469–476. https://doi.org/10.1007/978-3-642-16295-4_52

[7] Anind K Dey, Katarzyna Wac, Denzil Ferreira, Kevin Tassini, Jin-Hyuk Hong, and Julian Ramos. 2011. Getting closer - an empirical investigation of the proximity of user to their smart phones. *UbiComp* (2011), 163. https://doi.org/10.1145/2030112.2030135

[8] Daniel Kahneman, Alan B Krueger, David A Schkade, Norbert Schwarz, and Arthur A Stone. 2004. A Survey Method for Characterizing Daily Life Experience: The Day Reconstruction Method. *Science* 306, 5702 (Dec. 2004), 1776–1780. https://doi.org/10.1126/science.1103572

[9] Antti Kotanen, Marko Hännikäinen, and Timo Hämäläinen Leppäkoski, Helena. 2003. Experiments on Local Positioning with Bluetooth. *ITCC* (2003), 297–303. https://doi.org/10.1109/ITCC.2003.1197544

[10] Neal Lathia, Veljko Pejovic, Kiran K Rachuri, Cecilia Mascolo, Mirco Musolesi, and Peter J Rentfrow. 2013. Smartphones for Large-Scale Behavior Change Interventions. *IEEE Pervasive Computing* 12, 3 (2013), 66–73. https://doi.org/10.1109/MPRV.2013.56

[11] Shu Liu, Yingxin Jiang, and Aaron Striegel. 2014. Face-to-Face Proximity EstimationUsing Bluetooth On Smartphones. *IEEE Trans. Mob. Comput.* 13, 4 (2014), 811–823. https://doi.org/10.1109/TMC.2013.44

[12] G Mansell and K Curran. 2016. Location Aware Tracking with Beacons. *The 7th International Conference on Indoor Positioning and Indoor Navigation* (Oct. 2016), 4–7.

[13] Vivek Mhatre and Konstantina Papagiannaki. 2006. Using smart triggers for improved user performance in 802.11 wireless networks. *MobiSys* (2006), 246. https://doi.org/10.1145/1134680.1134706

[14] Shwetak N Patel, Julie A Kientz, Gillian R Hayes, Sooraj Bhat, and Gregory D Abowd. 2006. Farther Than You May Think - An Empirical Investigation of the Proximity of Users to Their Mobile Phones. *UbiComp* 4206, Chapter 8 (2006), 123–140. https://doi.org/10.1007/11853565_8

[15] Pew Research Center. 2019. Mobile Fact Sheet. https://www.pewinternet.org/fact-sheet/mobile/

[16] Jenny Röbesaat, Peilin Zhang, Mohamed Abdelaal 0001, and Oliver E Theel. 2017. An Improved BLE Indoor Localization with Kalman-Based Fusion - An Experimental Study. *Sensors* 17, 5 (2017), 951. https://doi.org/10.3390/s17050951

[17] Piotr Sapiezynski, Arkadiusz Stopczynski, David Kofoed Wind, Jure Leskovec, and Sune Lehmann. 2017. Inferring Person-to-person Proximity Using WiFi Signals. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 1, 2 (2017), 24–20. https://doi.org/10.1145/3090089

[18] Saul Shiffman, Arthur A Stone, and Michael R Hufford. 2008. Ecological Momentary Assessment. *dx.doi.org* 4, 1 (March 2008), 1–32. https://doi.org/10.1146/annurev.clinpsy.3.022806.091415

[19] Rui Wang, Fanglin Chen, Zhenyu Chen, Tianxing Li, Gabriella Harari, Stefanie Tignor, Xia Zhou, Dror Ben-Zeev, and Andrew T Campbell. 2014. StudentLife: Assessing Mental Health, Academic Performance and Behavioral Trends of College Students Using Smartphones. (2014), 3–14. http://doi.acm.org/10.1145/2632048.2632054

Appendix A ONLINE SURVEY

The purpose of this study is to understand the factors which impact proximity (distance) between users and their smartphones. Participants will be asked about their smartphone usage (or non-usage) as well as their smartwatch and smart device usage (if applicable). Participants can expect this survey to take 10 - 15 minutes. This survey is anonymous. However, if you would like to participate in a raffle for a chance to win a $50 Amazon gift card, you will be asked to provide your email address for prize retrieval.

Smart Phone

Q1: Do you own a smartphone? (Yes (Move to Q3), No (Move to Q2))

Q2: What are your reasons for not owning a smartphone? (Text input)

Q3: Which smartphone brand do you own? (Apple, Asus, Google, Huawei, LG, Microsoft, Motorola, Nokia, Samsung, Sony, Other)

Q4: What is the model of your smartphone? (Text input)

Q5: In what year did you start using a smartphone? (1995 - 2018)

Q6: How many hours in a day (24 hours) would you estimate that your smartphone is within arm's reach or closer? (1 - 24)

Q7: With what frequency do you forget the location of your phone each week? (0 times, 1-2 times, 3-4 times, 5 or more times)

Q8: In this section, a variety of circumstances are listed. For each circumstance, select how you decide on the proximity of your phone (distance) to yourself. (On my body (in hand, pocket), Within arm's reach (5ft or less), Within the same room (5-15 ft), Beyond room level (More than 15 ft), I don't think about it, N/A)

- Q8-1: In environments which may damage your phone (water, construction, extreme weather)

Q8-2: In International countries

Q8-3: In Public spaces (bus, parks)

Q8-4: During idle times

Q8-5: During instances where phone could be lost, damaged, or stolen (busy places, in presence of children)

Q8-6: When expecting to coordinate plans with others via phone

Q8-7: When you know you do not need your phone for any specific activity

Q8-8: When you make a quick trip (coffee break, bathroom)

Q8-9: When running errands (gas station, grocery shopping)

Q8-10: While performing routine activities in the home

Q8-11: While expecting contact via text, call, or other method

Q8-12: While socializing with others

Q8-13: While at work/school

Q8-14: While driving

Q9: Do any rules and regulations from outside authorities (e.g. church, work, school) affect your phone's proximity to you? Please describe. Example: Does your work require you to carry a cell phone at all times? Does your work prohibit you from carrying your cell phone with you during work hours? If so, where do you put it? (Text Input)

Q10: Do any self-imposed rules and regulations affect your phone's proximity to you? Please describe.

Smart Watch

Q1: Do you own a smartwatch? (Yes (Move to Q2), No (Move to Q12))

Q2: Which brand of smartwatch do you currently own? (Apple, Asus, Casio, Fitbit, Fossil, Motorola, Pebble Time, Samsung, Sony, Ticwatch, Other)

Q3: What is the model of your current smartwatch device? (Text input)

Q4: In which year did you first own a smartwatch? (1998 - 2018)

Q5: How many hours in a day (24 hours) would you estimate that your smartwatch is worn on your body? (1 - 24)

Q6: With what frequency do you forget the location of your smartwatch each week? (0 times, 1-2 times, 3-4 times, 5 or more times)

Q7: How many times per day do you take off your smartwatch? (0 times, 1-2 times, 3-4 times, 5 or more times)

Q8: Please describe any reasons for removing your smartwatch from your wrist. (Text input)

Q9: Select your top three reasons for using your smartwatch. (Aesthetics/style, Accessibility, Comfort, Convenience, Durability, Functionality, Portability, Price, Replace my smartphone, Quality, Social Pressure, Other)

Q10: How does your smartwatch usage supplement or replace your smartphone usage? (Text input)

Q11: If you have any applications that you prefer to use on your smartwatch instead of your smartphone please list the name of the applications and why. (Text input)(Move to Q13)

Q12: Are you interested in owning a smartwatch? (Yes, No)

Q13: Rate how much you agree with the following statement: "Smartwatches will eventually replace smartphones." (Strongly agree, Somewhat agree, Neither agree nor disagree, Somewhat disagree, Strongly disagree)

Smart Device

Q1: Do you own smart devices or wearables (e.g. Smart home assistant such as Amazon Alexa or Google home; smart thermostat, activity tracker, heart rate monitor, etc.)? (Yes (Move to Q2), No (Move to Q4))

Q2: Please list the smart devices you own. (Text input)

Q3: How does your smart device usage supplement or replace your smartphone or smartwatch usage? (Text input)

Q4: Is there anything else you'd like to share? (Text input)

Participant Information

Q1: What is your age? (Under 18, 18-24, 25-34, 35-44, 45-54, 55-64, 65-74, 75-84, 85 or older)

Q2: With which gender do you identify? (Male, Female, Other)

Q3: What is the highest degree or level of school you have completed? (No schooling completed, Nursery school to 8th grade, Some high school/no diploma, High school diploma/GED, Some college/no degree, Trade/technical/vocational training, Associate degree, Bachelor's degree, Master's degree, Professional degree, Doctorate degree)

Q4: What is your occupation? (Text input)